International Journal of Clothing Science and Technology

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Jirˇí Militky´ Vladimír Bajzík

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Surface roughness of heat protective clothing textiles

Jiří Militký and Vladimír Bajzík
Department of Textile Materials, Textile Faculty, Technical University of Liberec, Liberec, Czech Republic

Keywords *Surface roughness, Measurement, Fractals*

Abstract *The surface roughness is one of the main parts of hand prediction. Classical method of surface roughness measurements is based on the surface profile measurement. Characteristic of roughness is then variation coefficient of surface profile (surface height variation). The main aim of this work is to estimate the surface profile complexity by using variogram (structure function). The surface profile variation is classified to the group according to short- and long-range dependence. The concept of fractal dimension is proposed especially for long-term correlation cases. The applicability of the proposed approach is demonstrated on the typical heat protective clothing fabrics and compared with the results of surface roughness evaluated by the KES system.*

1. Introduction

Roughness of engineering surfaces has been traditionally measured by the stylus profiling method creation of surface profile called surface height variation (SHV) trace (Vandenberg and Osborne, 1992). This profile characterizes thickness (height) variation in selected direction. Modern methods are based on the image processing of surface images (Zhang and Gopalakrishnan, 1996). Surface irregularity of plain textiles has been identified by friction (Ajayi, 1992), contact blade (Ajayi, 1994; Kawabata, 1980), lateral air flow (Ajayi, 1988), step thickness meter (Militký and Bajzík, 2000) or subjective assessment (Stockbridge *et al.*, 1957).

Standard methods of surface profile evaluation are based on the relative variability characterized by the variation coefficient (analogy with evaluation of yarn's mass unevenness) (Meloun *et al.*, 1992) or simply by the standard deviation. This approach is used in Shirley software for evaluation of results for step thickness meter (Operation Manual, 1999). Characterization of roughness based on the mean absolute deviation (MAD) is the classical descriptive statistical approach. This statistical characteristic is useful for random SHV traces, where elements of SHV trace are statistically independent of each other. The SHV profile of a lot of fabrics has been identified as irregular and more structured. The descriptive statistical approach based on the assumptions of independence and normality leads to biased estimators if the SHV has short- or long-range correlations (Meloun *et al.*, 1992). Therefore, it is necessary to distinguish between standard *white Gauss noise* and more complex models. For description of short range correlations, the models based on the *autoregressive*

This work was supported by project LN 00 B090 of Czech Ministry of Education.

International Journal of Clothing Science and Technology
Vol. 15 No. 3/4, 2003
pp. 258-267

0955-6222
DOI 10.1108/09556220310478369

moving average are useful (Quinn and Hannan, 2001). The long-range correlations are characterized by the *fractal models* (Constantine and Hall, 1994; Mandelbrot and Van Ness, 1968). The *deterministic chaos* type models are useful for revealing chaotic dynamic in deterministic processes, where variation appears to be random, but in fact they are predictable (Ott *et al.*, 1994).

For the selection among the above-mentioned models, the power spectral density (PSD) curve evaluated from experimental SHV can be applied (Eke *et al.*, 2000). Especially, the fractal models are widely used for rough surface description (Whitehouse, 2001). For these models the dependence of log (PSD) on the log (frequency) should be linear. Slope of this plot is proportional to *fractal dimension* and intercept to the so-called *topothesy*. For, white noise has dependence of log(PSD) on the log(frequency) nearly horizontal plateau for all frequencies (the ordinates of PSD are independent and exponentially distributed with common variance (Ott *et al.*, 1994)). More complicated rough surfaces as a result of grinding can be modelled by the Markov type processes (Sacerdotti *et al.*, 2000). For these models the dependence of log(PSD) on the log(frequency) has plateau at small frequencies than bent down and are nearly linear at high frequencies.

The fractal type models were criticized by Whitehouse (2001), who concluded that the benefits are more virtual than real. On the other hand, the deeper analysis of rough surface should use a more complex model than the classical descriptive statistics. Greenwood (1984) proposed a technique based on the definition of local maxims (peaks) and derivation of peaks height distribution. A lot of recent works is based on the assumption that the stochastic process (Brownian motion) can describe thickness variation (Nayak, 1971). This work is devoted to the analysis of load required to move the blade on fabric surface $R(d)$ obtained from new accessory to tensile testing machine.

2. Surface profile evaluation

Kawabata (1980) constructed a measuring device for registering the SHV trace. The main part of this device is the contactor in the form of wire (diameter 0.5 mm). This contactor is moved at a constant rate 0.1 cm/s and SHV is registered on the paper sheet. The sample length, $L = 2\,\text{cm}$ is used. Characterization of roughness is based on the MAD (the classical descriptive statistical approach).

Similar approach is based on the measurement of $R(d)$ by Shirley step meter with replacement of measuring head by blade (Militký and Bajzík, 2001). We have constructed the simple accessory to the tensile testing machine. The principle is registration of the force $F(d)$ needed for tracking the blade on the textile surface. Roughly speaking, the $F(d)$ should be inversely proportional to the $R(d)$. In reality, the $F(d)$ profile is different due to small surface; deformation caused by the tracked blade. Output from measurements is sequence of loads $F(d_i)$. Variation of thickness $R(d_i)$ or loads $F(d_i)$ can be generally assumed as combination of random fluctuations (uneven threads, spacing between yarns, non-uniformity of production etc.) and periodic fluctuations caused by the repeated patterns (twill, cord, rib etc.) created by weft and warp yarns. For the description of roughness the characteristics computed from $R(d)$ or $F(d)$ in places $0 < d < T$ (T is maximum investigated sample length and M is number of places) are used. Especially, for weaves it is necessary to identify periodic component in $R(d)$ or $F(d)$ as well. For this purpose, the spectral analysis can be useful.

3. Surface roughness description

From the SHV or SFV trace it is possible to evaluate a lot of roughness parameters. Let us define roughness characteristics for SHV (the same equations are also valid for SFV). Classical roughness parameters are based on the set of points $R(d_j)$, $j = 1 \ldots M$ defined in the sample length interval L. The measurement points d_j are obviously selected as equidistant and then $R(d_j)$ can be replaced by the variable R_j. For the identification of positions in length scale, it is sufficient to know sampling distance $d_s = d_j - d_{j-1} = L/M$ for $j > 1$. The standard roughness parameters used frequently in practice are (Wu, 2000):

MAD. This parameter is equal to the mean absolute difference of surface heights from average value (R_a). For a surface profile, this is given by:

$$\mathrm{MAD} = \frac{1}{M}\sum_j |R_j - R_\mathrm{a}| \tag{1}$$

This parameter is often useful for quality control. However, it does not distinguish between profiles of different shapes. Its properties are known for the case when R_j's are independent identically distributed (iid) random variables.

Standard deviation (root mean square) value (SD). This is given by:

$$\mathrm{SD} = \sqrt{\frac{1}{M}\sum_j (R_j - R_\mathrm{a})^2} \tag{2}$$

Its properties are known for the case when R_j's are iid random variables. One advantage of SD over MAD is that for normally distributed data is simplicity of computation of confidence interval and realization of statistical tests. SD is always higher than MAD and for normal data $\mathrm{SD} = 1.25\,\mathrm{MAD}$. It does not distinguish between profiles of different shapes as well. The parameter SD is less suitable than MAD for monitoring certain surfaces having large deviations (corresponding distribution has heavy tail).

Mean height of peaks (MP). This is calculated as the average of the profile deviations above the reference value R (often $R = R_\mathrm{a}$). It is given as mean value of peaks P_i, $i = N_p$ where:

$$P_i = R_i - R \text{ for } R_i - R > 0 \text{ and } P_i = 0 \text{ elsewhere}$$

Mean height of valleys (MV). This is calculated as the average of the profile deviations below the reference value R (often $R = R_a$). It is given as mean value of valleys V_i, $i = N_v$ where:

$$V_i = R - R_i \text{ for } R_i - R < 0 \text{ and } V_i = 0 \text{ elsewhere}$$

The parameters MP and MV give information on the profile complexity. Exceptional peaks or valleys are not considered, but are useful in tribological applications.

The SD of profile slope (PS). This is given by:

$$\mathrm{PS} = \sqrt{\frac{1}{M}\sum_j \left(\frac{\mathrm{d}R(x)}{\mathrm{d}x}\right)_j^2} \tag{3}$$

The SD of profile curvature (PC). This quantity often called as waviness is defined by the similar way:

$$\mathrm{PC} = \sqrt{\frac{1}{M}\sum_j \left(\frac{\mathrm{d}^2R(x)}{\mathrm{d}x^2}\right)_j^2} \tag{4}$$

The slope and curvature are characteristics of a profile shape. The PS parameter is useful in tribological applications. The lower the slope the smaller the friction and wear. Also, the reflectance property of a surface increases in the case of small PS or PD.

Mean slope of the profile (MS). This is given by:

$$\mathrm{MS} = \frac{1}{M}\sum_j \left|\frac{\mathrm{d}R(x)}{\mathrm{d}x}\right|_j \tag{5}$$

Mean slope is an important parameter in several applications such as in the estimation of sliding friction and in the study of the reflectance of light from surfaces.

Ten point average (TP). This characteristic is defined as the average difference between the five highest peaks and five deepest valleys within a surface profile. The parameter TP is sensitive to the presence of high peaks or deep scratches in the surface and is preferred for quality control purposes.

These parameters are useful in the case of functional surfaces or for characterizing surface bearing and fluid retention and other relevant properties. For, the characterization of hand will probably be the best to use waviness PC. The characteristics of slope and curvature can be computed for the case of fractal surfaces from power spectral density, autocorrelation function or variogram. A set of parameters for profile and surface characterization are collected in (Nayak, 1971).

There exist a vast number of empirical profile or surface roughness characteristics suitable often in very special situations. Some of them are closely connected with characteristics computed from fractal models (fractal dimension and topothesy). Greenwood (1984) proposed a general theory for description of surface roughness based on the distribution of heights. The most common way to separate roughness and waviness is spectral analysis. This analysis is based on the Fourier transformation from space domain d to the frequency domain $\omega = 2\pi/d$.

For computation of the above-mentioned characteristics, the program DRSNOST in MATLAB has been created. The following characteristics are computed:

(1) Mean absolute deviation MAD;

(2) Mean profile slope MS;

(3) Standard deviation of profile slope PS;

(4) Standard deviation of profile curvature PC;

(5) Ten point average TP;

(6) Variation coefficient $CV = SD/R_{\mathrm{a}}$;

(7) Mean fractal dimension D_F;

(8) Initial fractal dimension D_{F_p}.

The computation of fractal dimensions is described in chapter 7.

4. Statistical analysis

A basic statistical feature of $R(d)$ is autocorrelation between distances. Autocorrelation depends on the lag h (i.e. selected distances between places of thickness evaluation). The main characteristics of autocorrelation is covariance function $C(h)$

$$C(h) = \mathrm{cov}(R(d), R(d+h)) = E((R(d) - E(R(d)))\,(R(d+h) - E(R(d)))) \tag{6}$$

and autocorrelation function ACF(h) defined as normalized version of $C(h)$:

$$\mathrm{ACF}(h) = \frac{C(h)}{C(0)} \tag{7}$$

The $E(x)$ denotes expected value of x. ACF is one of the main characteristics for the detection of short- and long-range dependencies in dynamic (time) series. It could be used for the preliminary inspection of data. The computation of sample autocorrelation directly from definition for large data is tedious. The technique of ACF creation based on the FFT is contained in the signal processing toolbox of MATLAB (procedure xcorr.m) [18] (Bloomfield, 2000). In spatial statistics, more frequent variogram (called often as structure function) is defined as one half variance of differences $(R(d) - R(d+h))$

$$\Gamma(h) = 0.5\,D[R(d) - R(d+h)] \tag{8}$$

Symbol $D(x)$ denotes variance of x. For stationary random process mean value is independent on lag h i.e. $E(R(h)) = m$ and then

$$\Gamma(h) = 0.5\,E(R(d) - R(d+h))^2 \tag{9}$$

The variogram is relatively simpler to calculate and assumes a weaker model of statistical stationarity, than the power spectrum. Several estimators have been suggested for the variogram. The traditional estimator is

$$G(h) = \frac{1}{2M(h)}\sum_{j=1}^{M(h)}(R(d_j) - R(d_{j+h})^2 \tag{10}$$

where $M(h)$ is the number of pairs of observations separated by lag h. Problems of bias in this estimate when the stationarity hypothesis becomes locally invalid have led to the proposal of more robust estimators.

5. Fractal dimension

Benoit Mandelbrot has coined the term fractal in the 1970s (Mandelbrot and Van Ness, 1968). Fractals have two interesting characteristics. First of all, fractals are self-similar on multiple scales, in that a small portion of a fractal will often look similar to the whole object. Second, fractals have a fractional dimension, as opposite to integer dimension of regular geometrical objects.

The fractional (fractal) dimension D can be evaluated by the following way: The number $N(\delta)$ of line segments of length δ needed to cover the whole curve in plane is measured. The length of curve is estimated as $L(\delta) = N(\delta)\delta$. In the limit $\delta \rightarrow 0$ the estimator $L(\delta)$ becomes asymptotically equal to the length of the curve, L, independently on δ. The Hausdorf-Besicovitch dimension D (fractal dimension) of this curve is the critical dimension for which the measure $M_d(\delta)$ defined as:

$$M_d(\delta) = N(\delta)\delta^d \tag{11}$$

changes from zero to infinity (Feder, 1988). The value of $M_d(\delta)$ for $d = D$ is often finite and therefore for sufficiently small δ:

$$N(\delta) \approx \delta^D \text{ or } L(\delta) \approx \delta^{1-D} \tag{12}$$

The fractal dimension is then computed as:

$$D = 1 - \frac{\log L(\delta)}{\log \delta} \tag{13}$$

For, random fractal is simpler to use power spectral density or related functions. Some techniques for fractal dimension computations are summarized, e.g. in Mannelqvist and Groth (2001). The methods for computation or Hurst coefficient is described in Wu (1999). In measurement of the surface profile (thickness variation $R(h)$), the data are available through one-dimensional line transect surface. Such data represent curve in plane. The fractal dimension D_F is then number between 1 (for smooth curve) and 2 (for rough curve).

Fractals are characterized by power type dependence of variogram and power spectral density. For a power law variogram:

$$\Gamma(h) \approx c|h|^H \tag{14}$$

where c is a constant. The Hurst exponent H, lies in the interval (0, 1). Where $H = 0$ this denotes a curve of extreme irregularity and $H = 1$ denotes a smooth curve. Exponents H and fractal dimension D are in fact related:

$$D_F = 2 - H \tag{15}$$

Fractal dimension is conventionally obtained through estimating the parameter from a LSE linear regression of the log-log transformation of equation (14). In practice, its behavior is expressed by equation (14) valid near origin. In general, D_F computed from this relation is denoted as an effective fractal dimension.

Based on these equations the program DRSNOST in MATLAB for estimation of fractal dimension from variogram has been constructed. From the first 12 points (excluding three points near origin) the initial fractal dimension D_{F_p} and from all points the mean fractal dimension D_F are computed.

6. Experimental part

The 54 flame retardant barrier textiles have been selected for investigation. They covered flame retardant finished cotton fabrics (satin, linen and twill patterns), fabrics created from heat resistant fibers (Nomex, FR Viscose and modacrylic fibers) and combinations of heat resistant fibers with flame retardant finished cotton. The $F(d)$ traces have been obtained by means of the above described accessory. The $R(d)$ traces have been obtained from KES device, and Kawabata mean roughness (MAD) was computed. The subjective hand SH was evaluated from judgment of 30 persons. They rated the fabrics to the 11-point scale. The subjective hand SH was computed as median of ratings divided by 11.

7. Results and discussion

For the investigation of mutual relations among subjective hand, classical characteristics of roughness (outputs 1-6 from DRSNOST program) and fractal characteristics of roughness (outputs 7-8 from DRSNOST program) the correlation map has been created. This map is shown in Figure 1(a). In the first

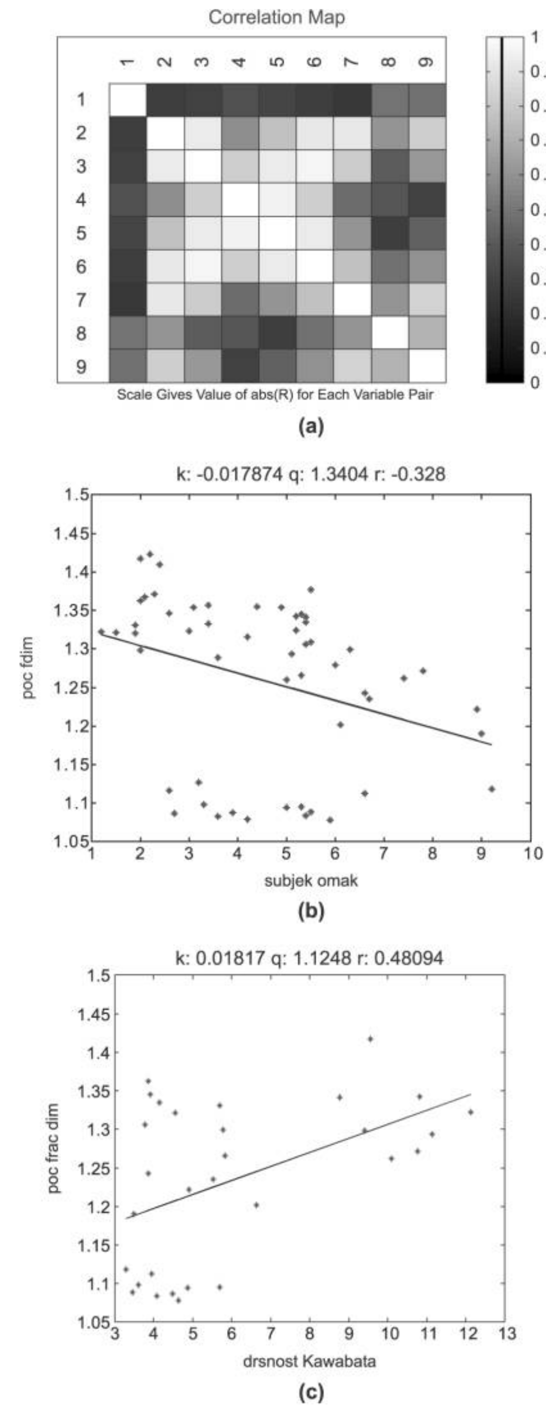

Figure 1.
(a) Correlation map of characteristics (first variable is SH); (b) relation between initial fractal dimension and subjective hand SH; (c) dependence between roughness from SFV (D_{F_p}) and Kawabata SHV (*MAD*)

column of this map are correlations of subjective hand with roughness characteristics. It is clear, that the correlations are not so high (black denotes no correlation and white denotes perfect linear relation). Maximum correlation is between subjective hand and fractal dimensions. There are correlations between some roughness characteristics as well. The dependence between subjective hand and initial fractal dimension D_{F_p} is shown in the Figure 1(b). It can be said that for these materials the roughness has a little influence on hand. The deeper analysis of the correlation map and partial relations between roughness characteristics lead to the following conclusions: MAD highly correlates with other roughness characteristics; MAD correlates with fractal dimensions as well, but some no linearity appears. Comparison of D_{F_p} calculated from SFV and Kawabata *MAD* from SHV is shown in Figure 1(c). Moderate correlation in Figure 1(c) indicates the differences between these two methods. One reason is the filtration of some frequencies realized automatically by the KES device.

8. Conclusion

The initial fractal dimension is probably most suitable for the complexity of roughness characterization. The analysis of SFV based on the DRSNOST program is more complex in reality. The more classical roughness characteristics and topothesy are computed as well and many other techniques of fractal dimension calculation are included.

References

Ajayi, J.O. (1988), "Some studies of frictional properties of fabrics", Doctoral thesis, University of Strathclyde, Glasgow.

Ajayi, J.O. (1992), "Fabric smoothness, friction and handle", *Textile Research Journal*, Vol. 62, pp. 87-93.

Ajayi, J.O. (1994), "An attachment to the constant rate of elongation tester for estimating surface irregularity of fabric", *Text. Res. J.*, Vol. 64, pp. 475-6.

Bloomfield, P. (2000), *Fourier Analysis of Time Series*, Wiley, NY.

Constantine, A.G. and Hall, P. (1994), *J. Roy. Stat. Soc.*, Vol. B56, p. 97.

Eke, A. *et al.*, (2000), *Eur. J. Physiol.*, Vol. 439, p. 403.

Feder, J. (1988), *Fractals*, Plenum Press, NY.

Greenwood, J.A. (1984), "A unified theory of surface roughness", *Proc. Roy. Soc. London*, Vol. A393, p. 133.

Kawabata, S. (1980), "The standardization and analysis of hand evaluation", *Text. Mach. Soc. Japan*.

Mandelbrot, B.B. and Van Ness, J.W. (1968), "Fractional Brownian motion, fractional noises and applications", *SIAM Review*, Vol. 10, p. 442.

Mannelqvist, A. and Groth, M.R. (2001), *Appl. Phys.*, Vol. A73, pp. 347-56.

Meloun, M., Militky, J. and Forina, M. (1992), "Chemometrics for analytic chemistry Vol. I", *Statistical Data Analysis*, Ellis Horwood, Chichester.

Militký, J. and Bajzík, V. (2000), "Description of thickness variation by fractal dimension", *Proc. Conf. STRUTEX 2000*, December Liberec (2000) (in Czech).

Militký, J. and Bajzík, V. (2001), "Characterization of textiles surface roughness", *Proc. 7th Int. Asian Textile Conference*, August 2001, Hong Kong.

Nayak, P.R. (1971), *Trans. ASME: J. Lub. Tech.*, Vol. 93F, p. 398.

Operation Manual (1999), Shirley.

Ott, E., Sauer, T. and Yorke, J.A. (Eds) (1994), *Copying with chaos*, Wiley, NY, USA.

Quinn, B.G. and Hannan, E.J. (2001), *The Estimation and Tracking of Frequency*, Cambridge University Press, Cambridge.

Sacerdotti, F., Griffiths, B.J., Butler, C. and Benati, F. (2000), *Proc. Inst. Mech. Engfs.*, Vol. 214B, p. 811.

Stockbridge, H.C. *et al.*, (1957), "The subjective assessment of the roughness of fabrics", *Journal of the Textile Institute*, Vol. 48, pp. T26-34.

Vandenberg, S. and Osborne, C.F. (1992), *Wear*, Vol. 159, pp. 17-30.

Whitehouse, D.J. (2001), *Wear*, Vol. 249, p. 345.

Wu, J. (1999), *Wear*, Vol. 230, p. 194.

Wu, J. (2000), *Wear*, Vol. 239, p. 36.

Zhang, C. and Gopalakrishnan, S. (1996), "Fractal geometry applied to on line monitoring of surface finish", *Int. J. Mach. Tools Manufact.*, Vol. 36, pp. 1137-50.